Evaluating the Applicability of Soil Moisture-based Metrics for Gauging the Resiliency of Rainfed Agricultural Systems in the Midwestern United States

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Abstract: Measuring and improving resiliency is the key goal of climate risk management in rainfed agriculture. Currently, available metrics are generally used to qualitatively measure the resilience of agricultural systems at broader scales. Moreover, these metrics showed non-linear responses to climate variability, thus often fail to capture the temporal dynamics of resilience at field scales. Our objective for this study is to combine a few soil moisture-based metrics to gauge the resiliency of three promising rainfed agricultural treatments, namely the no-till, organic, and reduced input treatments against the conventional treatment. These treatments have been established at the Kellogg Biological Station Long-Term Ecological Research (KBS-LTER) experiment in a randomized complete block design with six blocks per treatment. All four of these treatments consisted of maize (*Zea mays*)-soybean (*Glycine max*)-winter wheat (*Triticum aestivum*) in rotation. Long-term (1993-2018) soil moisture data from this experiment was collected to compute the soil moisture metrics while the total crop biomass, crop yield, and soil organic carbon data were statistically analyzed to evaluate the robustness of the metrics to gauge the resiliency of these systems. Results have shown that, among the soil moisture metrics, the mean relative difference, the Spearman's rank correlation coefficient, and soil water deficit index were suitable, while the index of temporal stability was not suitable to gauge the resiliency of different rainfed agricultural systems. The no-till treatment was identified as the most resilient treatment in terms of soil moisture retention, effectiveness for drought mitigation, and crop yields. Meanwhile, the reduced input treatment was the least resilient in terms of soil water conservation and drought recovery. The results of this study can be extended to other Midwest regions of the United States and similar climatological areas around the world.

Keywords: Agricultural Drought; Climate Risk Management; Mean Relative Difference; Soil Water Deficit Index; Resiliency

1. Introduction

Rainfed agriculture systems account for 80 percent of the croplands in the world and contribute to nearly 60 percent of total food production (FAO, 2017). Meanwhile, in the United States, about 94 percent of farmland acres are considered rainfed agriculture (USDA, 2014). Rainfed agricultural systems in the United States are economically important, ecologically diverse, technologically advanced, and are most common in the eastern half of the mainland where annual precipitation is greater than 500mm. In this region, the majority of the corn and soybean crops are produced from these systems, either as a monocrop or in rotation. The productivity of these crops steadily increased in the past as a result of genetic improvements (about 70%) and management interventions (about 30%). Moreover, with the development of glyphosate-resistant crop varieties, adoption of conservation agriculture practices such as no-tillage has been substantially increased to counteract the problems of soil erosion, nutrient leaching and runoff, and yield instability (Franzluebbers et al., 2011).

Regardless of this overall increase in productivity, crop yields have been shown to be vulnerable to interannual variability in the climate (Hatfield et al., 2018; Hatfield, 2012; Lesk et al., 2016; Thornton et al., 2014). Like in other areas around the world, changes in the regional climate in the Midwestern states result in increasing the frequencies of extreme events such as droughts, floods, and heatwaves (Andresen et al., 2012; Hatfield et al., 2018; Pryor et al., 2014). The water availability for rainfed agriculture is primarily controlled by the seasonal pattern of precipitation (intensity and frequency) and its interactions with the soil-plant-atmosphere continuum (Rost et al., 2009). This makes rainfed crop production much more vulnerable to the effects of climate variability and extremes. For example, the flash drought in 2012 devastated major crops and economic base of rainfed farms in the Midwestern region (Fuchs et al., 2012; Mallya et al., 2013; Otkin et al., 2018, 2016). Flash droughts are associated with decreased precipitation and humidity, increased solar radiation, and elevated temperatures, leading to reduced availability of soil water to crops (Ford and Labosier, 2017). As highlighted by Rippey, (2015), due to this drought development, corn yield in the US has fallen for three consecutive years from 2010-2012 for the first time since 1928-1930. These climate extremes will have substantial impacts not only on the national economy but also on international markets (Boyer et al., 2013).

Resilience can be generally defined as a capability of a system to recover from stressors (Holling, 1973). Therefore, climate-resilience can be considered as the ability of a system to maintain its structures and patterns of behavior in the face of climate perturbations. This allows the system to continue to provide its services, which in the case of agriculture, is the growth and yield of crops (Tendall et al., 2015; Urruty et al., 2016; Walker et al., 2004). It also refers to the ability of a system to develop capacities to cope with, adapt, and potentially transform the appropriate management practices to face the challenges of the climate shocks and extremes (Bousquet et al., 2016). Specific to rainfed agriculture, climate-resilience can be used to describe the ability of the components of the system to recover from water stress (Tow et al., 2011). This could be achieved by implementing management interventions that will keep the soil moisture at relevant levels in a way that extreme climatic events shall not reduce the crop yields significantly. Such actions to enhance the climate-resilience in rainfed agriculture can be broadly categorized as genetic interventions, informed decisions, and agronomic interventions.

Genetic interventions involve developing new germplasm with improved tolerance to environmental stresses such as drought and heat stress and crop genotypes with phenological adjustments to avoid such stresses (Ainsworth and Ort, 2010; Ceccarelli et al., 2010; Davies et al., 2011). Adoption of these genotypes with improved stress tolerance has increased the climate-resilience of corn and soybean production systems around the world (Cairns et al., 2012; Chapman et al., 2012; Sadok and Sinclair, 2011). *Informed decisions* refer to the utilization of seasonal climate forecast information (Hansen et al., 2011; Meinke et al., 2006). Forecast products such as those of NOAA's Climate Prediction Center (e.g., three-month outlooks) can potentially influence most of the agronomic and genetic interventions. *Agronomic interventions* may include, adjustment of planting and harvesting times, altering fertilization rates and irrigation practices (Howden et al., 2007; Nouri et al., 2017; Rurinda et al., 2015), mulching(Erenstein, 2003; Qin et al., 2015), crop diversification and agroforestry (Altieri et al., 2015; Gan et al., 2015; Lin, 2011; Mbow et al., 2014) and adoption of conservation agriculture (Delgado et al., 2013; Michler et al., 2019). There is also evidence for the improvement of climate-resilience under organically managed agricultural systems (Scialabba and Müller-Lindenlauf, 2010; Tuomisto et al., 2012) due to the enhancement in soil quality and reduction in environmental impacts.

In this study, we are mainly focusing on agronomic interventions, especially conservation agriculture as climate-resilient practice. Conservation agriculture comprises of three management principles: minimum soil disturbance/no-till, permanent soil cover by crop residues/cover crops, and crop rotation (Hobbs et al., 2008; Pittelkow et al., 2015a). These conservation practices are adopted at various intensities and combinations in the Midwestern states to provide varying degrees of resilience to climate shocks and extremes (Denny et al., 2019). In comparison to conventional tillage, the no-till/zero-tillage systems showed the highest level of climate-resilience as a result of improved water availability and soil quality, that helps to avoid substantial reductions in crop yields during extreme climatic events (Delgado et al., 2013; Harrington and Tow, 2011; Michler et al., 2019). In contrast, some other studies (e.g., Pittelkow et al., 2015a; Powlson et al., 2014) have shown that no-till reduces crop yields compared to conventional tillage and their potential for climate-resilience is limited. Interestingly, Pittelkow et al. (2015b), in their comprehensive review, highlighted that no-till, when combined with the other two principles of conservation agriculture (residue retention and crop rotation), significantly increases the crop yields in rainfed systems. This could be due to the ability of the system to capture snow, reduction of runoff and soil evaporation (with the retention of crop residues), and creation of better soil structure and rooting patterns through crop rotations to store more water in the root zone (Franzluebbers et al., 2011; O'Leary et al., 2011).

To evaluate responses of varying agronomic interventions of climate-resilience practices, there is a need for quantification metrics for system resiliency. Resilience metrics can be used to measure the level of improvement of a system towards sustainable states, track thresholds of potential concerns, and help with assessments on how the system is being managed (Quinlan et al., 2016). The Committee on Sustainability Assessment (COSA) stated that gauging resilience generally involves a holistic approach that incorporates social, economic, and environmental dimensions of resilience (COSA, 2017). Because of the complexity and interactions in these three dimensions, food system resilience is often assessed qualitatively (Toth et al., 2016). However, qualitative assessments are region-specific and subject to variations in assumptions. Therefore, multiple tools have been developed to evaluate the climate resilience of food production systems in many parts of the world (Douxchamps et al., 2017). These tools have often been applied to large socioeconomic units (e.g., households/communities/administrative regions/national scale). For example, the Resilience Index Measurement and Analysis Model (RIMA) developed by the Food and Agriculture Organization of the United Nations (FAO, 2016), is increasingly used to measure the climate-resilience of agricultural communities in many African countries (Serfilippi and Ramnath, 2018). Other such tools are Community Based Resilience Assessment (CoBRA) developed by the United Nations Development Program (UNDP, 2013), the Self-evaluation and

Holistic Assessment of climate Resilience of farmers and Pastoralists (SHARP) used by FAO (Choptiany et al., 2017), Community-based Risk Screening Tool-adaptation and Livelihood (CRiSTAL) developed by the International Institute for Sustainable Development (IISD, 2014), the Climate Vulnerability and Capacity Analysis (CVCA) developed by Care International (Care, 2009) and the Resilience, Adaptation and Transformation Assessment Framework (RATALF) developed by The Commonwealth Scientific and Industrial Research Organization (O'Connell et al., 2015).

In general, these tools use indices known as resilience metrics to evaluate the flexibility of a system. Means and variance of agricultural production (Di Falco and Chavas, 2008), crop yields (Birthal et al., 2015; Martin and Magne, 2015), profit (Browne et al., 2013; Komarek et al., 2015; Seo, 2010), revenue (Kandulu et al., 2012; Rigolot et al., 2017; Tibesigwa and Visser, 2015), labor productivity (Komarek et al., 2015), crop failure (Jones and Thornton, 2009), dietary diversity (Dillon et al., 2015), farming risks (Komarek et al., 2015), agricultural gross domestic product (Hsiang and Jina, 2014), and expenditure for food consumption/food security (Alfani et al., 2015) have been used as resilience metrics. These metrics are often used in combination and have shown non-linear responses to climate variability depending upon various characteristics of farms and farmers (Di Falco and Chavas, 2008; Tittonell, 2014). Despite the growing knowledge in this area, there is still no consensus on how resilience should be measured and no universal tool available to quantify resilience at different scales. Moreover, existing tools and frameworks often fail to capture the spatial and temporal dynamics of resilience (Dixon and Stringer, 2015; Douxchamps et al., 2017).

In order to address these challenges, there is a need for new metrics to address the complexity in agricultural systems while being simple enough to be measured and adopted by individual farmers. Therefore, we propose a new measure to overcome these challenges and constraints by providing a case-specific definition of resilience and confining our focus to long-term agronomic performance (soil moisture, growth, and yield of crops) under different rainfed agricultural systems at an experimental farm scale. However, it is important to note that this study is only focusing on farm-scale resiliency and therefore is not considering other sociological/institutional characteristics that are important beyond farm-scale, which can be evaluated through existing resilience metrics, which were discussed earlier. In order to achieve this goal, three objectives need to be satisfied: 1) rank the relative resilience of different rainfed agricultural systems using the metrics of temporal dynamics of soil moisture; 2) evaluate the robustness of the soil moisture metrics of temporal dynamics to growth and yield under climate extremes; and 3) compare the effectiveness of different rainfed agricultural systems on reducing agricultural drought severity.

2. Materials and Methods

2.1 Overview of Methodology

Root zone soil moisture is the key determinant of productivity in rainfed agricultural systems (Jägermeyr et al., 2016). The ability of a system to store a substantial amount of soil moisture is one of the key indicators of resilience, as recommended by COSA (2017). In this study we applied a combination of soil moisture-based metrics to gauge the resiliency of rainfed agricultural systems. Long-term (1993-2018) agricultural experiment data on soil moisture, total crop biomass, crop yield, and soil organic carbon were collected, which provides an excellent opportunity to conduct an exhaustive evaluation of resiliency in agricultural systems. We hypothesized that a rainfed agricultural system has a higher degree of resilience if it can maintain above-average soil moisture; thus, this relative resilience will beneficially affect the yields, especially during drought periods. However, the assumption of above-average soil moisture has an upper limit, especially during wet periods which can prevent agricultural operations such as harvesting. We test this hypothesis using soil moisture-based metrics in four differently managed long-term rainfed row crop treatments, namely, conventional treatment (CON), no-till treatment (NT), reduced input treatment (RI), and organically managed treatment (OR). These soil moisture-based metrics include three metrics of the temporal stability of soil moisture and an agricultural drought index. The soil moisture temporal dynamics metrics were selected to evaluate the relative resilience of different rainfed agricultural treatments (Objective 1), then we examined the robustness of these soil moisture metrics for different crops under climate extremes (i.e., dry and wet years) during the growing season. The results of this section can prove whether the soil moisture temporal dynamics metrics can be used to evaluate the resiliency of different agricultural systems as measures of growth and yield (Objective 2). Finally, an agricultural drought index was selected to evaluate the effectiveness of different rainfed agricultural treatments on reducing the agricultural drought severity (Objective 3).

2.2 Study Location and Site Description

This study was conducted at the Kellogg Biological Station (KBS), where the Long-Term Ecological Research (LTER) experiment is implemented to evaluate the performance of different annual and perennial crops under varying management intensity gradients (Robertson and Hamilton, 2015). KBS is located in Southwest Michigan at 288 m AMSL, within the northern boundary of the U.S. Corn Belt (42.41˚ N, 85.37˚ W). For the period of 1981-2010, the mean annual air temperature is 10.1 ˚C, and the mean annual precipitation is 1,005 mm, with 511 mm of the total precipitation falling as rain during the summer growing season (May-September) (NCEI, 2019). The evapotranspiration in this region is water-limited during the warmer part of the year and energy-limited during the colder months (Mcvicar et al., 2012). The soil of this experimental station is classified as fine-loamy, mixed, mesic Typic Hapludalf (Kalamazoo loam series) developed on glacial till and outwash (Syswerda and Robertson, 2014). The texture of the Ap horizon (0-30 cm) of this soil is loam or sandy loam (43% sand, 38% silt, and 19% clay). The pH, bulk density, and total soil carbon are 5.5, 1.6 g cm^{-3}, and 12.85 g kg^{-1}, respectively (Crum and Collins, 1995). The Main Cropping System Experiment (MCSE), established in 1988 (Figure 1), is comprised of seven model ecosystems namely, four annual row crop systems with different management intensity (treatments), Poplar (*Populus deltoides* × *P. nigra*), continuous Alfalfa (*Medicago sativa*), and an early successional vegetation community (Robertson and Hamilton, 2015). For this study, we selected the first four annual row crop treatments that were designed in a management intensity gradient.

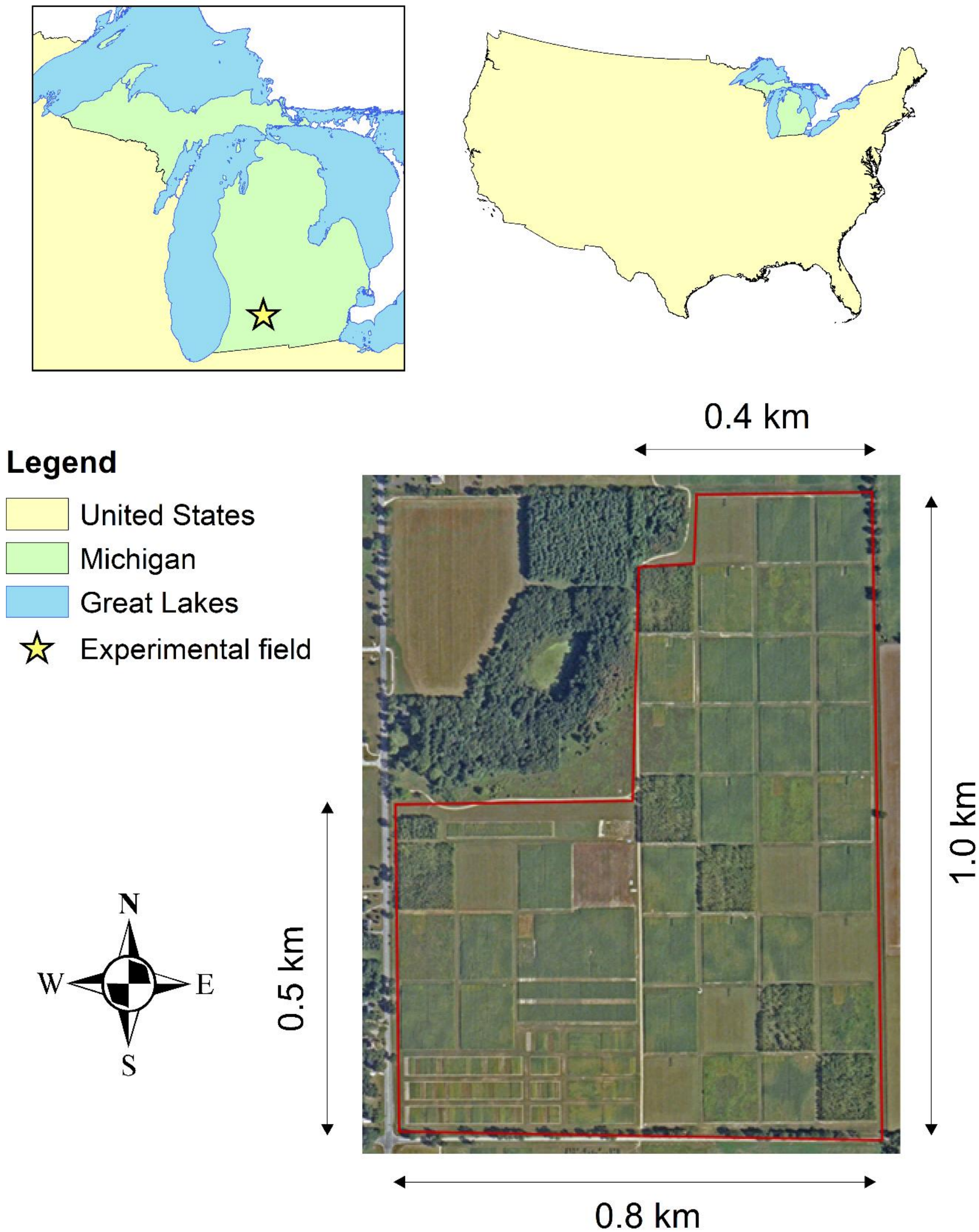

Figure 1. The experimental fields of the Main Cropping System Experiment (MCSE) at the Kellogg Biological Station (KBS) in Michigan, United States.

Crops were established and measurements began in 1989. All agricultural systems within the experiment have been managed as rainfed and each of them is assigned to six replicates (blocks) of one-ha, plots (87 × 105 m) in a randomized complete block design. The four annual row crop treatments consisted of maize (*Zea mays*)-soybean (*Glycine max*)-winter wheat (*Triticum aestivum*) rotations managed as (i) conventional treatment (CON), (ii) no-till treatment (NT), (iii) reduced input treatment (RI), and (iv) organically managed (USDA certified organic) treatment (OR). The conventional treatment is considered as the control. This allows us to measure the resilience of selected agricultural systems in comparison to the conventional system. The reasons behind the selection of the conventional treatment as control are; 1) majority of the croplands (>85% globally and >65% in the United States) are under conventional agriculture (Kassam et al., 2019) and 2) conventional system has been identified as the significant contributor of pollutions to the environment (Foley et al., 2011; Meier et al., 2015).

All row crop treatments were planted and harvested at the same time. A routine experimental design was followed only from 1993; therefore, we confined this study for the period of 1993-2018. The detailed description of the four annual row crop treatments is presented in the Supplementary Materials section (Table S1).

2.3 Data Collection

To achieve the objectives of this research, gravimetric soil moisture, soil organic carbon, total crop biomass, and yield were measured for the period (1993-2018) from the experimental plots at KBS. Gravimetric soil moisture data were collected, and then respective bulk density data were used to convert it into volumetric soil moisture. This volumetric soil moisture data was used to calculate the metrics of soil moisture temporal dynamics to evaluate the relative resilience of different rainfed agricultural treatments (Objective 1). In addition, soil organic carbon data were collected to explore its associations with observed soil moisture dynamics. Total crop biomass and yield data were collected to evaluate the robustness of the soil moisture metrics to gauge resiliency to climate extremes in terms of growth and yield of crops (Objective 2). Finally, the volumetric soil moisture data was used to calculate the drought index to evaluate the effectiveness of different rainfed agricultural treatments on reducing the agricultural drought severity (Objective 3).

Soil moisture: Gravimetric soil moisture measurements began in 1989 in all MSCE agricultural treatments. These measurements were employed each year, typically biweekly throughout the growing season (April-October). Soils were collected from five permanent sampling stations established in each replicate (plot). Two soil cores were taken from each sampling station using soil augers to represent 0-25 cm depth. These ten samples were then composited by the physically mixing of individual soil cores taken within a replicate into one homogeneous sample. Composite soil samples were sieved through a 4 mm screen to remove debris and homogenize the sample. About 40-50 g of sieved composite samples were taken into soil moisture cans, and then oven-dried to a constant weight, at least 24 hours at 105 ˚C. The gravimetric soil moisture (θ_g) was calculated as follows (Reynolds, 1970);

$$\theta g = \frac{Weight\ of\ moist\ soil - Weight\ of\ dry\ soil}{Weight\ of\ dry\ soil} \tag{1}$$

Bulk density: Bulk density is used to convert gravimetric soil moisture into volumetric soil moisture. In this study, we used the gravel-free bulk density values measured using a root sampler (ELKJAMP, Inc., Wageningen, Netherlands) with 7.95 cm diameter at 25 cm depth (Blake and Hartge, 1986). Bulk density (*BD*) was calculated as follows (Carter and Gregorich, 2008);

$$BD = \frac{Weight\ of\ dry\ soil}{Volume\ of\ soil\ core\ (Cylindrical\ volume)} \tag{2}$$

Bulk density measurements were available for MCSE during the years of 1996, 2001, 2010 and 2013. Therefore, bulk density measurements from the years 1996, 2001, 2010 and 2013 were used to convert gravimetric soil moisture measurements for the periods of 1993-2000, 2001-2009, 2010-2012, and 2013-2018, respectively. equation 3 (Evett, 2008) was used to convert gravimetric soil moisture into volumetric soil moisture (θ_v), assuming the density of water is 1 gcm^{-3}.

$$\theta v = \theta g \times BD \tag{3}$$

Soil organic carbon: Soil organic carbon from the surface soils (0-25 cm) for each treatment and respective replicates was available for the period of 1989-2001. Even though the measurements have been made for total soil carbon (organic and inorganic forms), extensive testing of KBS surface soils has shown soil inorganic carbon to be non-detectable; thus, total soil carbon is identical to total organic carbon. To measure the total soil carbon, subsamples were oven-dried at 60 ˚C for at least 48 hours until no further mass loss occurred. Dried and finely grounded soil samples are weighed into small foil capsules which were combusted in an automated CHN (carbon, hydrogen and nitrogen) analyzer that measured the amount of released CO_2 using gas chromatography (Jimenez and Ladha, 1993). Soil carbon values were expressed as a percentage of carbon in dry soil. We utilized these soil organic carbon values to explore its associations with soil moisture dynamics.

Crop biomass and yield: Total crop biomass was measured from 1993 at peak growth of biomass per growing season. Aboveground biomass hand-clipped within 1 m^2 sampling quadrat at each of the five sampling stations per replicate. Sampling quadrat was designed to accommodate the variations in row spacing for different crops. The dimension of the sampling quadrat for corn was 1.5 m × 0.66 m, whereas soybean and wheat were sampled from a 2 m × 0.5 m quadrat. Collected biomass was oven-dried at 60 ˚C for 48 hours and weighed. Seed yield of crops was measured for the entire plot by machine harvesters at the end of each growing season when crops reached maturity. The standardized moisture content for yield measurement was 15.5% for corn and 13% for wheat and soybean.

2.4 Calculating the Metrics of Temporal Dynamics of Soil Moisture to Examine the Relative Resilience of Different Rainfed Agricultural Treatments

Metrics of the temporal dynamics of soil moisture are the mean relative difference (MRD), index of temporal stability (ITS), and non-parametric Spearman's rank correlation coefficient (r_s). MRD is used to present the relative ranks of different rainfed agricultural treatments in terms of root zone soil moisture content, ITS is used to show the variability of the MRD ranking over the growing season and r_s was used to indicate the persistence of the relative MRD ranks over the period of study (Jacobs et al., 2004; Joshi et al., 2011; Vachaud et al., 1985). In the past, temporal stability analysis of soil moisture was used to identify time-stable points or representative locations to employ monitoring networks/sensors (Barker et al., 2017; Brocca et al., 2010; Starks et al., 2006; Zhou et al., 2007) and to validate remote sensing soil moisture products (Cosh et al., 2008; Jacobs et al., 2004; Joshi et al., 2011; Wagner et al., 2008). In other studies, the metrics were used to study the spatiotemporal dynamics of soil moisture in a hillslope (Gao et al., 2016; Liu et al., 2018), under different land use (Hu et al., 2010) or in diverse soil layers (Gao and Shao, 2012; He et al., 2019). In this study, we will use these metrics to gauge the relative resilience of different rainfed agricultural treatments.

Mean Relative Difference: MRD was introduced by Vachaud et al. (1985) to study the temporal stability of spatially measured soil moisture. The mean relative difference (equation 4) together with the index of temporal stability (equation 7) have been used in the spatiotemporal analysis of soil moisture (Gao and Shao, 2012; He et al., 2019; Joshi et al., 2011; Liu et al., 2018). Here, we use these metrics to evaluate the spatiotemporal dynamics of soil moisture across different agricultural treatments. The MRD (% cm^3/cm^3) for treatment in a particular growing season (year) is defined as:

$$MRD = \frac{1}{Nt}\sum_{t=1}^{Nt}[(\Theta v - \overline{\Theta})/\ \overline{\Theta}] \tag{4}$$

$$\overline{\Theta} = \frac{1}{NT}\sum_{T=1}^{NT}\Theta v \tag{5}$$

where, θv is the volumetric soil moisture (% cm^3/cm^3) measured in a treatment T at time t. $\overline{\Theta}$ is the mean volumetric soil moisture of all treatments. N_T is the number of treatments. Nt is the number of soil moisture measurements (sampling days) during the particular growing season.

A negative MRD value indicates that the treatment is *drier* than the field-averaged soil moisture, whereas a positive MRD value signifies that the treatment is *wetter* than the field mean soil moisture (Joshi et al., 2011).

Variance of Relative Difference: The variance of the relative difference for each treatment is calculated as:

$$VRD = \frac{1}{nt-1}\sum_{t=1}^{Nt}\left\{\frac{\Theta v-\overline{\Theta}}{\overline{\Theta}} - MRD\right\}^2 \tag{6}$$

The MRD quantifies the deviation of the soil moisture in a particular treatment, and the VRD quantifies the accuracy of that measurement (Joshi et al., 2011). Here we calculated VRD to derive ITS in the next step (equation 7).

Index of Temporal Stability: ITS can be derived by considering both MRD and VRD (He et al., 2019; Jacobs et al., 2004; Liu et al., 2018); therefore, ITS represents both bias and accuracy metrics.:

$$ITS = \sqrt{MRD^2 + VRD} \tag{7}$$

In a rank ordered MRD and ITS plot, treatments with MRD values close to zero and with smaller ITS values can be considered temporally more stable than the others with the mean difference of zero and large ITS values (He et al., 2019; Joshi et al., 2011; Liu et al., 2018). However, our intention in this work is to find out relatively *wetter* treatment (i.e., positive MRD). By using relative ranks as the performance metric, instead of an absolute soil moisture value, we account for interannual variability of root zone soil moisture. Because we hypothesized that if an agricultural system can hold more soil moisture due to conservation practices (e.g., no-till) during the growing period than a conventional system, it would positively be affecting the growth and yield of crops in rainfed agricultural systems.

Non-parametric Spearman's rank correlation coefficient: The non-parametric Spearman's rank test (Vachaud et al., 1985) was used to examine the persistence of MRD ranks over the 26-year study period for each treatment. The r_s is expressed as:

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(R_{ij} - R_{ik})}{n(n^2-1)} \qquad (8)$$

where, R_{ij} is the rank of MRD in treatment i on the year j, R_{ik} is the rank of MRD in treatment i on the following year k, and n is the number of years. The r_s was calculated for each agricultural system where r_s of 1, for any treatment, represents the MRD having the same rank between the years j and k. Therefore, high values of r_s (values close to 1) represent high temporal persistence of relative ranking over the study period (Liu et al., 2018).

2.5 Evaluate the Sensitivity of the Mean Relative Difference of Soil Moisture to Climate Variability and its Reflections on Crop Growth and Yield in Different Treatments

Long-term experimental data on soil moisture, total crop biomass, crop yield, and soil organic carbon were collected from KBS-LTER data catalog and processed using a python script in Wing Pro Version 7.1.2 (Wingware, Cambridge, Massachusetts, USA) and Microsoft Excel Version 2016 (Microsoft Corporation, Redmond, Washington, USA). In this study, a mixed model (Milliken and Johnson, 2009) was used to explore the statistical significance of random and fixed effects of independent variables on selected response variables.

The statistical model for evaluating the effects of treatment, climate variability and year on selected response variables (i.e., MRD, total crop biomass and yield) was specified as;

$$y_{ijk} = \mu + clim + trt_i + yr_k + trt_i \times clim + blk_j(yr_k) + trt_i \times yr_k + e_{ijk} \quad (9)$$

where, y_{ijk}: is the vector of observation (response variable) collected for the i^{th} treatment, within j^{th} block on the k^{th} year. μ: is the overall mean, *trt*: is the fixed effect of treatments, which represents different agricultural systems, *blk*: is the random effect of the replications (blocks) nested within years, *clim*: is the fixed effect of the climate variability (dry, normal and wet), *yr*: is the random effect of the year, *trt* × *clim*: is the interaction between the effects of treatment and the fixed effect of climate variability, *trt* × *yr*: is the interaction between the effects of treatment, the random effect of the year, and *e* is the residual. The effect of seasonal mean temperature was also initially included in the statistical model as a fixed effect; however, the temperature effect and all the interaction terms with temperature were non-significant at $p \leq 0.05$ for all studied response variables. Thus, we decided not to include the effect of seasonal mean temperature in the final statistical model. The non-significant effect of seasonal mean temperature was most likely a result of a little coefficient of variation (CV = 4.8%) observed for this continuous variable. The normality of the residuals and homogeneity of variances were checked for each response variable (Milliken and Johnson, 2001). The data for all response variables were normal, and their variances were homogeneous.

Analyses were performed by crop (separately for each crop), using PROC GLIMMIX procedure (Milliken and Johnson, 2009) in SAS software version 9.4 (SAS Institute Inc. Cary, North Carolina, USA). Fixed effects were tested using the F-test (Steel et al., 1980), and random effects were tested using the Wald test for covariance (Wald, 1943). The Tukey Test for mean separation was performed when significant differences were detected for the fixed effects (Lee and Lee, 2018), and significant differences were evaluated at the 0.05 probability level (Steel et al., 1980). Pearson's correlation analysis (Weaver et al., 2017) was performed using MINITAB 15 (Minitab, LLC. State College, PA, USA) to determine the relationship between MRD and soil organic carbon.

2.6 Compare the Effectiveness of Different Treatments on Reducing Agricultural Drought Severity

Agricultural drought is defined as a period of soil moisture deficiency resulting in the shortage of precipitation that occurs for a few weeks of duration (Esfahanian et al., 2017). Therefore, we decided to evaluate the impacts of these treatments on agricultural drought severity and occurrence using the Soil Water Deficit Index (SWDI). SWDI was considered for this study since it requires fewer inputs and is more widely used than other agricultural drought indices such as Palmer Moisture Anomaly Index (Alley, 1984; Palmer, 1965), Soil Moisture Deficit Index (Narasimhan and Srinivasan, 2005), and Evapotranspiration Deficit Index (Narasimhan and Srinivasan, 2005). In addition, when time-series soil moisture measurements are available from the root zone, SWDI can be successfully implemented at the field scale to assess agricultural drought (Martínez-Fernández et al., 2015) with the additional information on field capacity and permanent wilting point of that particular soil. Ultimately, the evaluation of the agricultural drought severity will enable us to gauge the relative resilience of different rainfed agricultural systems.

Categorization of climate variability: Total seasonal precipitation (April-October) for the period of 30 years (1989-2018) was collected from the KBS weather station located within the experimental site, and the probability distribution was calculated to categorize the climate variability, namely dry years (cumulative probability less than 33.3%), normal years (cumulative probability between 33.3% and 66.6%) and wet years (cumulative probability greater than 66.6%) as shown in Figure 2.

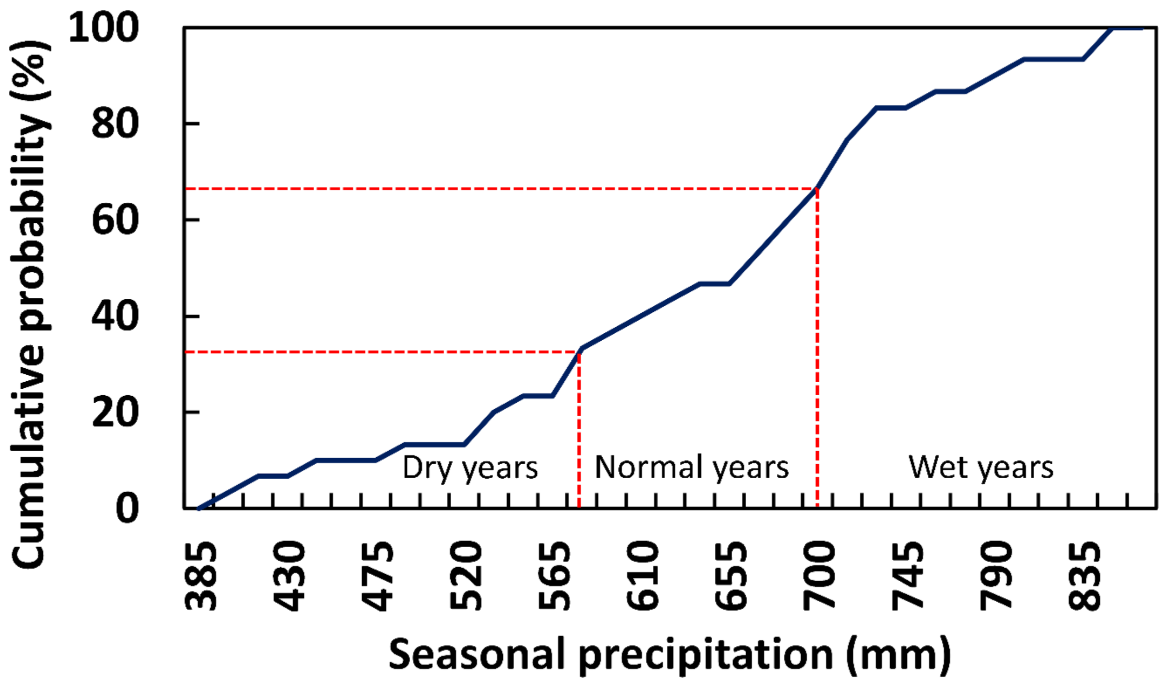

Figure 2. Cumulative probability distribution of seasonal precipitation for the period of 30 years (1989-2018) at KBS weather station.

Based on the frequency analysis explained above, dry years were categorized as the years that the seasonal precipitation ≤ 580 mm, wet years were categorized as the years that the seasonal precipitation ≥ 700 mm and normal years were categorized as the years that seasonal precipitation is in between. Classification of the entire experimental period (1993-2018) into the above climate variability categories for each crop in the rotation is given in Table 1.

Table 1. Climate variability for each crop in the rotation

Crop	Categories of climate variabilities	Years
Corn	Dry years	1996, 1999, 2002, 2005
	Normal years	1993, 2014, 2017
	Wet years	2008, 2011
Soybean	Dry years	1997, 2012
	Normal years	2003, 2009
	Wet years	1994, 2000, 2006, 2015, 2018
Wheat	Dry years	1995, 1998, 2007
	Normal years	2004, 2010, 2016
	Wet years	2001, 2013

Soil Water Deficit Index (SWDI): The soil water deficit index is an agricultural drought indicator developed by Martínez-Fernández et al. (2015) based on water deficit accumulation or soil water storage. SWDI is the fraction between the differences of i) volumetric soil moisture and field capacity, and ii) plant available water content, which is the difference between field capacity and permanent wilting point. This fraction is then multiplied by 10 to obtain SWDI (equation 10), and the respective drought severity levels:

$$SWDI = \left\{\frac{\theta v-\theta_{FC}}{\theta_{FC}-\theta_{WP}}\right\} \times 10 \tag{10}$$

where, θ_v is the volumetric soil moisture (% cm^3/cm^3), θ_{FC} is the field capacity (% cm^3/cm^3) of the soil, and θ_{WP} is the permanent wilting point (% cm^3/cm^3). The SWDI is calculated for the root zone on all the dates of soil moisture measurement for each treatment during the growing season. The median volumetric soil moisture of six replicates was used to calculate SWDI. Since the soil texture of this experimental station is fine-loamy, we selected the field capacity value of 27% and the wilting point of 12% as proposed by Ratliff et al. (1983) and Hanson et al. (2000). When SWDI is positive, the soils have excess water; when it equals zero, the soil is at field capacity (i.e., no water deficit). A negative MRD indicates the drought, and the water deficit is absolute (wilting point) when the SWDI reaches ≤ -10. After this point, the soil water content falls below the lower limit of plant-available water (Savage et al., 1996). Based on calculated SWDI, drought severity can be categorized as "no drought" if SWDI > 0, as "mild" if 0 > SWDI > -2, as "moderate" if -2 > SWDI > -5, as "severe" if -5 > SWDI > -10, and as "extreme" if -10 > SWDI (Martínez-Fernández et al., 2015).

The number of droughts in each severity category was added for each treatment during the study period 1993-2018, and the percentage of drought events was calculated and compared under the categories of climate variability (dry, normal and wet years). Moreover, SWDI for the entire study period (1993-2018) was organized in descending order for each treatment to perform probability analysis as described by Alizadeh (2013). This would allow analyzing the behavior of drought severity under different treatments in response to climate variability.

3. Results and Discussion

3.1 Ranking the relative resilience of different rainfed agricultural treatments using the metrics of temporal dynamics of soil moisture

3.1.1 Ranking the resilience of soil moisture in different treatments:

As discussed earlier, we hypothesize that if soil moisture in an agricultural system can remain wetter than the conventional (control) system over the growing season due to treatment, it would beneficially affect the growth and yield of crops in rainfed agriculture. Therefore, treatments were ranked on the ascending order of MRD for the study period (1993-2018) and presented together with ITS for each climate variability category as dry years (Figure 3), normal years (Figure S1), and wet years (Figure S2).

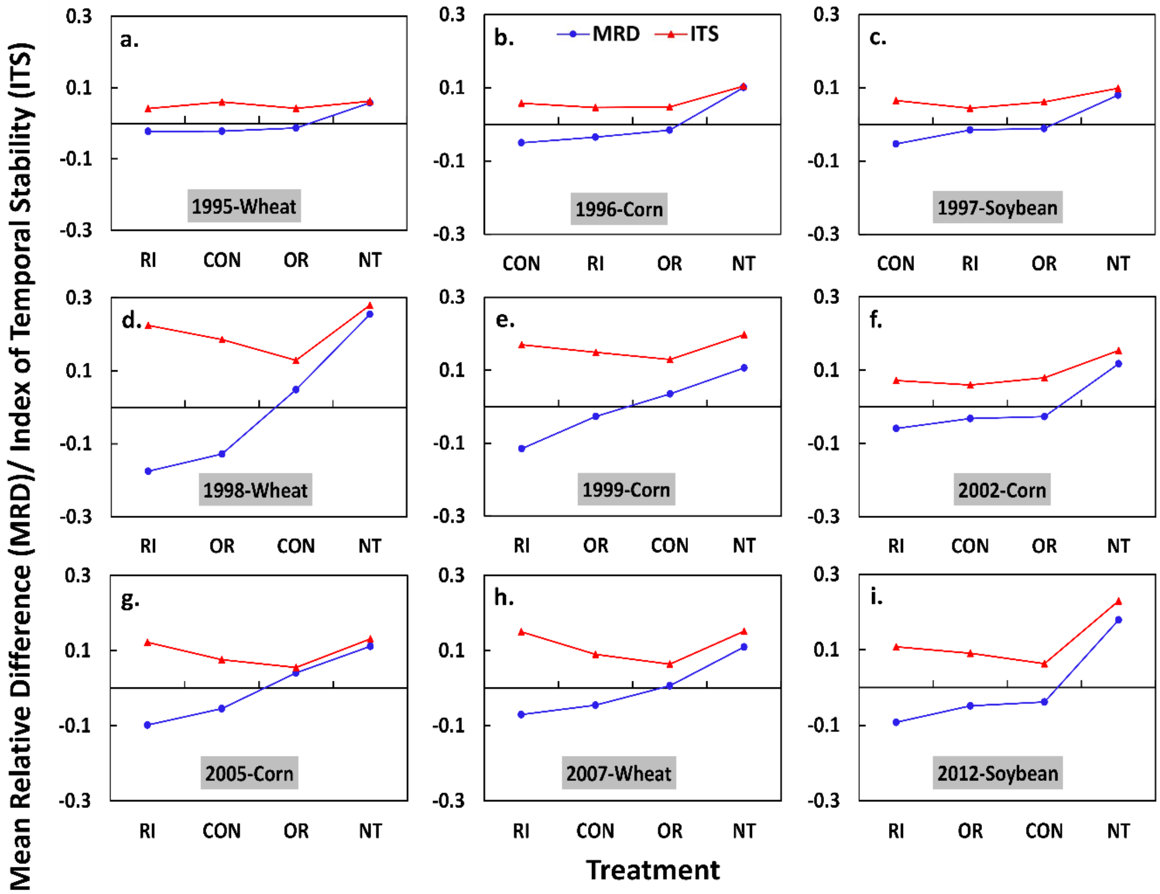

Figure 3. Ranked MRD of volumetric soil moisture and ITS for each treatment during the dry years. Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

According to the relative positions of MRD during dry years (Figure 3), a no-till treatment maintained higher soil moisture (and higher MRD) than a conventional treatment. Similarly, the organic treatment always performed better than the reduced input treatment, while the conventional treatment performed better than the reduced input treatment in the majority of years. During normal and wet years, no-till and organic treatments were better than the conventional treatment, while reduced input treatment performed equally to the conventional treatment in most of the normal and wet years (Figures S1 and S2).

Table 2 presents the number of occurrences in each rank, based on MRD and the relative positions of MRD (either negative or positive) for different categories of climate variability. The rankings are based on the ascending order of MRD in which a wetter system is represented by the highest-ranking (rank=4). During dry and normal years, in the majority of observations, the reduced input, the conventional, the organic, and the no-till treatments were ranked one through four, respectively. This indicates that the no-till treatment was the wettest and the organic treatment was wetter than the conventional treatment; however, the reduced input treatment was drier than the conventional treatment during dry and normal years. During wet years, the majority of the times conventional treatment represented the lowest rank (i.e., rank 1) thus it was the driest of the treatments, while the no-till treatment represented the highest rank (i.e., rank 4) thus the wettest of the treatments. Organic and reduced input treatments fell in between; however, the organic treatment was still wetter than the reduced input treatment.

Concerning the relative positions of MRD, the no-till treatment was wetter (100% of years having positive MRD) than all other treatments during dry, normal, and wet years. The organic treatment performed similar to the conventional treatment, while the reduced input treatment was drier than conventional treatment in dry years (100% of years having negative MRD). During normal and wet years, the organic treatment was wetter in ≥50% of years, which was higher than the conventional treatment. Meanwhile, the reduced input treatment performed equally to the conventional treatment during normal and wet years.

Table 2. Relative positions and ranking based on MRD, and their respective percentages for each agricultural system under each climate variability category

Category of climate variability	**Treatment***	**Relative positions of MRD** (Percent of the total years)		**Ranking based on MRD** Number of occurrences in each rank (Years)			
		MRD<0	MRD>0	1	2	3	4
Dry years	CON	77.8	22.2	2	4	3	0
	NT	0	100	0	0	0	9
	RI	100	0	7	2	0	0
	OR	77.8	22.2	0	3	6	0
Normal years	CON	87.5	12.5	2	5	1	0
	NT	0	100	0	0	1	7
	RI	87.5	12.5	6	2	0	0
	OR	50	50	0	1	6	1
Wet years	CON	100	0	5	4	0	0
	NT	0	100	0	0	0	9
	RI	100	0	3	5	1	0
	OR	44.4	55.6	1	0	8	0

*CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

The no-till treatment showed the highest level of soil moisture resilience in all categories of climate variability. This can be due to improved soil water dynamics. In the no-till treatment, a greater amount of crop residues was retained in the soil compared to the conventional treatment (Palm et al., 2014; Pittelkow et al., 2015b). As a result, organic matter and biotic activity significantly increased in the topsoil, which leaded to greater wet aggregate stability and macropore connectivity while reducing soil compaction (Blanco-Canqui and Ruis, 2018; Palm et al., 2014; Perego et al., 2019). Therefore, water infiltration increased, surface runoff, and soil evaporation decreased, which resulted in an increased amount of plant-available water (Liu et al., 2013; Palm et al., 2014; Thierfelder et al., 2013; Thierfelder and Wall, 2009). The impact of the no-till treatment on higher soil moisture and water use efficiency was also evident under irrigation (Gathala et al., 2013; Grassini et al., 2011). The average measured soil organic carbon in our experiment for the 13-year period (1989-2001) supports these arguments where the no-till treatment had significantly higher soil organic carbon than the conventional treatment (Figure S3). Additionally, the organic treatment and the reduced input treatment also had significantly higher soil organic carbon compared to the conventional treatment. However, accumulation of soil organic carbon in tilled reduced input and organic treatments were unlikely and may be a result of leguminous winter cover crop established in these treatments (Robertson et al., 2014). We also found a significant positive correlation between the mean relative difference (MRD) of volumetric soil moisture and the soil organic carbon (Figure S4). This highlights the increase in soil moisture retention with increasing soil organic carbon, which was observed in the no-till and the organic treatments. This is one of the main reasons for the increasing yield of crops with increasing soil organic carbon (Oldfield et al., 2019) unless other resources were limited. The next best treatment in terms of soil moisture resilience was the organic treatment. This can be due to increased biological activity such as an abundance of earthworms that could beneficially affect the soil water dynamics; however, earthworm activity will be limited in other systems as a result of the application of herbicides (Bai et al., 2018). Moreover, leguminous winter cover cropping may also have beneficially affected the soil water dynamics in the organic system (Basche et al., 2016). Even though the reduced input system had a leguminous winter cover crop, it had the lowest soil moisture resilience because of the impacts of herbicide on soil structure by reducing soil biological activities (Basche and DeLonge, 2019).

As we look for an agricultural system with higher MRD, most of the time, the system with greater MRD also had higher ITS (Figures 3, S1, and S2). However, under a few instances, lower MRD could obtain a higher ITS. This can be explained by Equation 7 in which the ITS is always a positive value regardless of whether MRD is a positive or negative number. Therefore, ITS is not a suitable metric for gauging the resilience of an agricultural system as related to soil moisture temporal dynamics in a growing season.

3.1.2 Temporal persistence of soil moisture in different treatments:

Spearman's rank correlation coefficient (r_S) of different treatments for the duration of the study (1993-2018) is shown in Figure 4. Accordingly, the no-till treatment showed the highest temporal persistence ($r_S \approx 1$), highlighting its ability to maintain greater resilience of soil moisture among other treatments for the long-term (26-years). The conventional treatment showed the lowest temporal persistence. This is due to its ranking of the MRD, which behaves differently in different years (Figures 3, S1, and S2). Thus, the ability of the conventional treatment to maintain the resilience of soil moisture for an extended period is limited. The temporal persistence of the organic treatment and the reduced input treatment fell in between conventional and no-till treatments; however, the organic treatment performed a little better than the reduced input treatment. Therefore, the ability of the organic treatment to maintain the resilience of soil moisture for a long period was greater than the reduced input treatment. This observation is in support of the long-term effects of the no-till treatment in soil moisture conservation (Bai et al., 2018; Lampurlanés et al., 2016). Moreover, Castellini et al. (2019) detected a significantly higher number of micropores under the long-term no-till treatment compared to the conventional treatment. This can be another reason for the highest temporal persistence of soil moisture in the no-till treatment. Meanwhile, the moderate level of temporal persistence of soil moisture observed for organic and reduced input treatments can be attributed to increased soil moisture conservation with the winter cover crop applied to these treatments (Basche et al., 2016). Cover crops are also beneficial in reducing annual deep drainage and soil evaporation (Yang et al., 2020), thereby increasing soil water availability in the root zone.

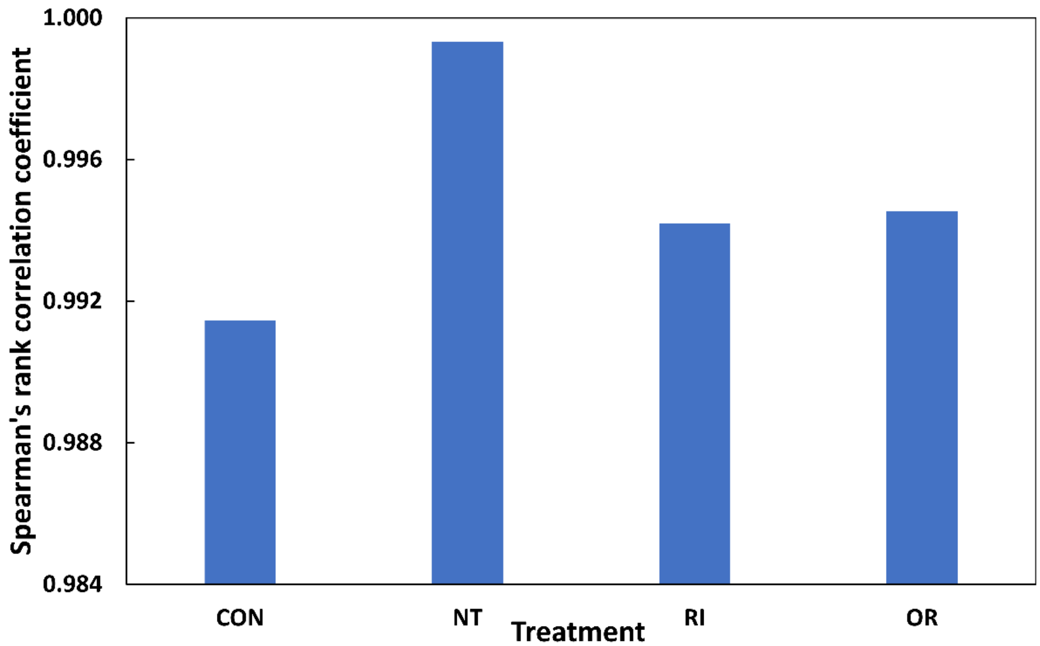

Figure 4. Spearman's rank correlation coefficient of different treatments for the duration of the study. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

3.2 Evaluating the effects of treatments and climate variability on mean relative difference of soil moisture and its reflections on crop growth and yield of crops

The mixed model (equation 9) explained in Section 2.5 was used to analyze the MRD, total biomass (at peak growth), and yield, considering them as response variables for individual crop types. The probability of the effects on the above response variables on each crop is presented in Table S2. Accordingly, the effect of treatments (*trt*) on MRD was strongly significant (p<0.0001) for all crops. However, the effect of climate variability (*clim*), year (*yr*), and interaction terms (*trt* × *clim* and *trt* × *yr*) were not significant. This means that MRD can be used to differentiate the impacts of different treatments regardless of climate variabilities and the random yearly effects. For total biomass and yield the effect of treatment (*trt*) was strongly significant (p<0.0001) in corn and wheat while it was significant ($p<0.05$) in soybean. Therefore, we first compared the treatments against the means of MRD, means of total biomass, and means of yield for each crop type in Table 3.

Table 3. The means of MRD, total biomass and yield for different treatments and crop types*

Treatment	Corn			Soybean			Wheat		
	MRD	Total biomass ($Mgha^{-1}$)	Yield ($Mgha^{-1}$)	MRD	Total biomass ($Mgha^{-1}$)	Yield ($Mgha^{-1}$)	MRD	Total biomass (Mgha-1)	Yield (Mgha-1)
CON	-0.0549^{c}	14.26^{a}	6.78^{b}	-0.0551^{c}	5.33^{a}	2.40^{b}	-0.0202^{b}	8.07^{a}	3.74^{a}
NT	0.1121^{a}	15.08^{a}	7.80^{a}	0.1055^{a}	5.46^{a}	2.83^{a}	0.1293^{a}	8.45^{a}	3.90^{a}
RI	-0.0602^{c}	14.45^{a}	6.81^{b}	-0.0492^{c}	5.21^{ab}	2.62^{ab}	-0.0742^{b}	6.86^{b}	3.38^{b}
OR	0.0136^{b}	10.14^{b}	4.30^{c}	0.0072^{b}	4.81^{b}	2.33^{b}	-0.0204^{b}	4.59^{c}	2.08^{c}

* Means with the same letter in each column are not significantly different at $p<0.05$. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment

The comparison of treatments versus means of MRD (Table 3) showed that the no-till treatment had significantly higher MRD than the conventional treatment, which was ultimately reflected on the yield where it was significantly greater under the no-till treatment in corn and soybean. However, significantly higher MRD was not reflected in the growth where the biomass under the no-till treatment was not significantly different from the biomass under the conventional treatment. MRD in the reduced input treatment was not significantly different from the conventional treatment, which was reflected in the growth and yield of corn and soybean, where their biomass and yield were not significantly different (Table 3). Meanwhile, the MRD in the organic treatment was significantly greater than that in the conventional system for corn and soybean (Table 3). This was not reflected in the growth as it was significantly lower in the organic treatment for both crops. Furthermore, the yield of corn was significantly lower in the organic treatment than the conventional treatment. In contrast, the yield of soybean in the organic treatment was not significantly different from the yield in the conventional treatment. In wheat, MRD was significantly higher in the no-till treatment than the conventional treatment; however, growth and yield were not significantly different. Moreover, MRD in the reduced input and organic treatments was not significantly different from the conventional treatment in wheat; however, growth and yield were significantly lower in these two treatments than the conventional treatment.

In addition to significant treatment effects (*trt*), the interaction between treatment and climate variability (*trt* × *clim*) was also significant for the total biomass and yield of crops (Table

S2). The occurrence of treatment by climate interaction (*trt* × *clim*) highlights that the performances of treatments change in different categories of climate variability; thus, worthy of an investigation. As shown in Figure S5, the cereals (corn and wheat) presented the highest growth and largest grain yield in the normal years, while the wet years produce higher growth and yield for soybean. Furthermore, we are particularly interested in the total biomass and yield performances of treatments under dry extreme of the climate variability. Total biomass of corn and soybean were not different among the treatments (Figure S5; a and b) during dry years. However, the no-till treatment had equivalent total biomass for wheat to that in the conventional treatment, while wheat growth was smaller in the reduced input and organic treatments (Figure S5; c). The no-till treatment produces higher yields than the conventional treatment for soybean and wheat during dry years (Figure S5; e and f) while corn yield in the no-till treatment was similar to that in the conventional treatment (Figure S5; d). Dry year yields of corn and soybean under the reduced input treatment and the organic treatment were comparable to the yields under the conventional treatment (Figure S5; d and e); however, these treatments did not perform well on the yield of wheat compared to the conventional treatment (Figure S5; f). Furthermore, the interaction between treatment and year (*trt* × *yr*) was also significant for the total biomass and yield of corn (Table S2). The occurrence of treatment by years interaction (*trt* × *yr*) is expected due to the number of years evaluated (26-years). In addition, this can be originated from interannual variations on other above- and below-ground environmental variables (e.g., solar radiation, vapor pressure deficit, and nutrient dynamics) which could also affect the growth and yield but were not included in the model (equation 9) used for this study.

In summary, significantly greater soil moisture retention, as quantified by MRD under the no-till treatment, was reflected on the significantly higher yields in corn and soybean than the conventional treatment when averaged across all the years. Moreover, the no-till soybean and wheat produced substantially higher yields than the conventional soybean and wheat during dry years. Similar to our study, significantly higher yields under the no-till treatment were also observed in several previous studies when combined with crop residue retention in long-term crop rotations (Corbeels et al., 2014; Deines et al., 2019; Pittelkow et al., 2015b; Rusinamhodzi et al., 2011). Moreover, Syswerda et al. (2012) found significantly lower nitrate leaching loss under the no-till treatment than the conventional treatment in this same experiment at KBS-LTER. Hence, the no-till treatment has the ability to use a greater amount of nitrogen in the process of yield formation.

Although the organic treatment had significantly greater MRD in corn and soybean than the conventional treatment, it did not produce significantly higher biomass or yield. However, organic soybean yield was equivalent to the conventional treatment even during dry years. Significantly higher MRD for no-till and organic treatments in corn and soybean than the conventional treatment signifies a greater soil moisture retention over the growing season under no-till and organic treatments. As previously discussed, this can be attributed to the improvement in soil physical properties and soil organic carbon with these conservation systems (Hobbs et al., 2008; Valkama et al., 2020; Verhulst et al., 2010; Williams et al., 2017). Additionally, the decrease in evaporation, increase in infiltration, and the ability to store more soil moisture under no-tillage produces greater soil water storage (Blevins et al., 1971; Lal et al., 2012; Lampurlanés et al., 2016). Meanwhile, the major reason behind the significant growth and yield reduction, especially in cereal crops (i.e., corn and wheat) with the organic treatment versus the other treatments, was nitrogen deficiency as organic treatment lacks exogenous nitrogen fertilizer application (Robertson et al., 2014). Growth and yield reduction was evident even if though higher soil water retention was shown to be higher for organic treatment than the conventional and reduced input treatments in our study. Interestingly, the yield of soybean in the organic treatment was comparable to that in the conventional and reduced input treatments even during dry years. This is because soybean has a synergistic relationship with nitrogen fixing bacteria, which reside on its roots and fix atmospheric nitrogen (Hungria and Mendes, 2015).

The equal performance of MRD in the reduced input treatment to the conventional treatment was reflected as the equivalent growth and yield of corn and soybean but not in wheat. In wheat, growth and yield were significantly lower in the reduced input treatment than the conventional treatment. Although reduced input treatment had the potential for soil quality improvement as a result of leguminous winter cover crop, this potential was limited because of herbicide and inorganic fertilizer application that substantially reduced the activities of soil biota (Bai et al., 2018; Tsiafouli et al., 2015). Therefore, the reduced input treatment performed inferior to the organic treatment on MRD in corn and soybean even though its performance was comparable to the conventional treatment. Equal performance of the reduced input treatment to the conventional treatment on crop growth and yield of corn and soybean was due to its equal performance on soil moisture retention, as it was shown in this study. Nonetheless, the growth and yield of wheat in the reduced input treatment were significantly lower than the conventional treatment. This is associated to the lack of nitrogen to wheat as it was planted in the fall immediately following the soybean harvest, which left a relatively low amount of nitrogen-rich crop residue for the wheat crop in the reduced input treatment, whereas corn and soybean followed nitrogen-fixing red clover winter cover crop (Robertson et al., 2014) that can supplement a reduced rate of nitrogen fertilizer application. This proves the ability of the winter red clover cover crop (Gentry et al., 2013; Vyn et al., 2000) to supply sufficient nitrogen to the reduced input system.

Interestingly, the coefficient of variation (CV) of total crop biomass and yield for different treatments under two extremes of climate variability (i.e., dry and wet) showed that the no-till treatment had the lowest CV values among other treatments except for wheat during wet years (Table S3). The lowest CV value indicates fewer variations, hence greater stability of growth and yield of these crops, which also highlights the resilience of the no-till treatment. This finding was in agreement with that of Verhulst et al. (2011), where they demonstrated that higher soil moisture retention under the zero-tillage resulted in a more stable agronomic system than the conventional system. In contrast, Rusinamhodzi et al. (2011) argued that yield stability was not substantially improved by the no-till system.

3.3 Comparing the effectiveness of different treatments on reducing agricultural drought severity

According to the classification of drought severity (Martínez-Fernández et al., 2015), the drought categories that are crucial for crop production are moderate, severe, and extreme. This is because the loss of soil moisture as a percentage of total plant available water is 20-50%, 50-100%, and 100% for moderate, severe, and extreme droughts, respectively (Martínez-Fernández et al., 2015). These losses of plant available soil moisture are translated to *some* crop damages under moderate drought, *likely* crop damages under severe drought, and *major* crop damages under extreme drought (Svoboda et al., 2002). Mild drought is not associated with significant crop damages; therefore, the effectiveness of different treatments on reducing moderate, severe, and extreme droughts are only assessed here.

In general, the numbers of severe and extreme drought events were decreased in all treatments when climate variability shifted from dry to wet (Figure 5). This is because increasing precipitation improves the availability of soil moisture to crops, thus reduces severe and extreme categories of agricultural drought, while increasing the drought events with lower severity (i.e., moderate/mild) or no drought. In terms of having drought-free events/no drought, no-till treatment is superior and organic treatment is better than the conventional treatment, while reduced input treatment is the worst. For example, the no-till treatment and the organic treatment had 467% and 67% higher drought-free events than the conventional treatment, respectively, during dry years, while the reduced input treatment had no drought-free events during dry years. The above observations were also noticed during normal and wet years where the no-till treatment and the organic treatment had substantially higher drought-free events than the conventional treatment, while the reduced input treatment had substantially lower drought-free events than the conventional treatment. Moreover, the effectiveness of the no-till system, especially on reducing moderate, severe, and extreme drought events is much higher than any other treatment irrespective of climate variability. During dry years where the drought can be prominent, the no-till treatment had 4%, 23%, and 57% lower severity than the conventional treatment, respectively, for the moderate, severe, and extreme droughts.

The effectiveness of the organic system on reducing moderate, severe, and extreme drought events is still better than the conventional system. The percentages of moderate and severe drought events in the organic treatment were 20% and 17% lower than the conventional treatment during dry years, respectively. Nonetheless, the effectiveness of the reduced input system is broadly limited. The reduced input treatment had 12% and 50% higher moderate and extreme drought events than the conventional treatment during dry years, respectively. However, it had 10% lower severe drought events than the conventional treatment during the dry years (Figure 5).

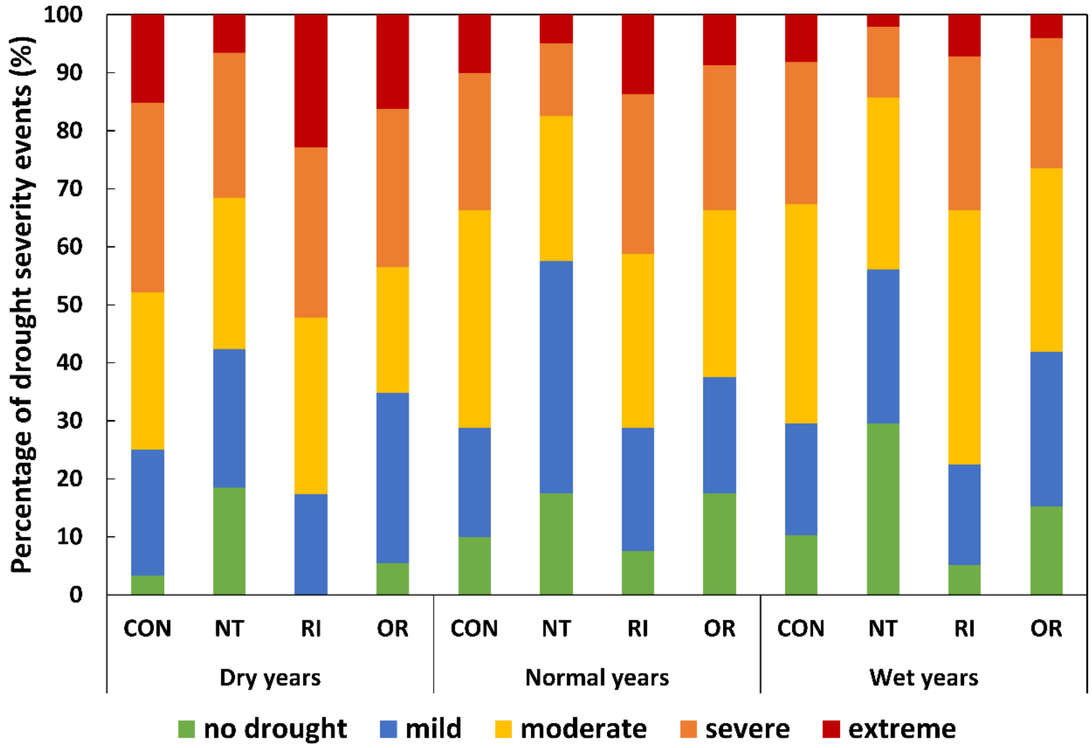

Figure 5. Percentage of agricultural drought severity events based on different treatments and climate variabilities during the experimental period (1993-2018). Note: The numbers of soil moisture measurements (events) available to calculate the percentage of different drought severities in the dry, normal, and wet years were 92, 80, and 98, respectively. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

Probability analysis of SWDI for the entire experimental period showed that no-till treatment has the highest probability (22%) to have drought-free events (Figure 6). Meanwhile, the organic, the conventional, and the reduced input treatments are ranked next with a probability of 12.5%, 7.8%, and 4%, respectively. The no-till treatment and the organic treatment had substantially lower probabilities under the impactful drought events (i.e., moderate, severe, and extreme) than the conventional treatment, while these probabilities were larger in the reduced input treatment (Figure 6).

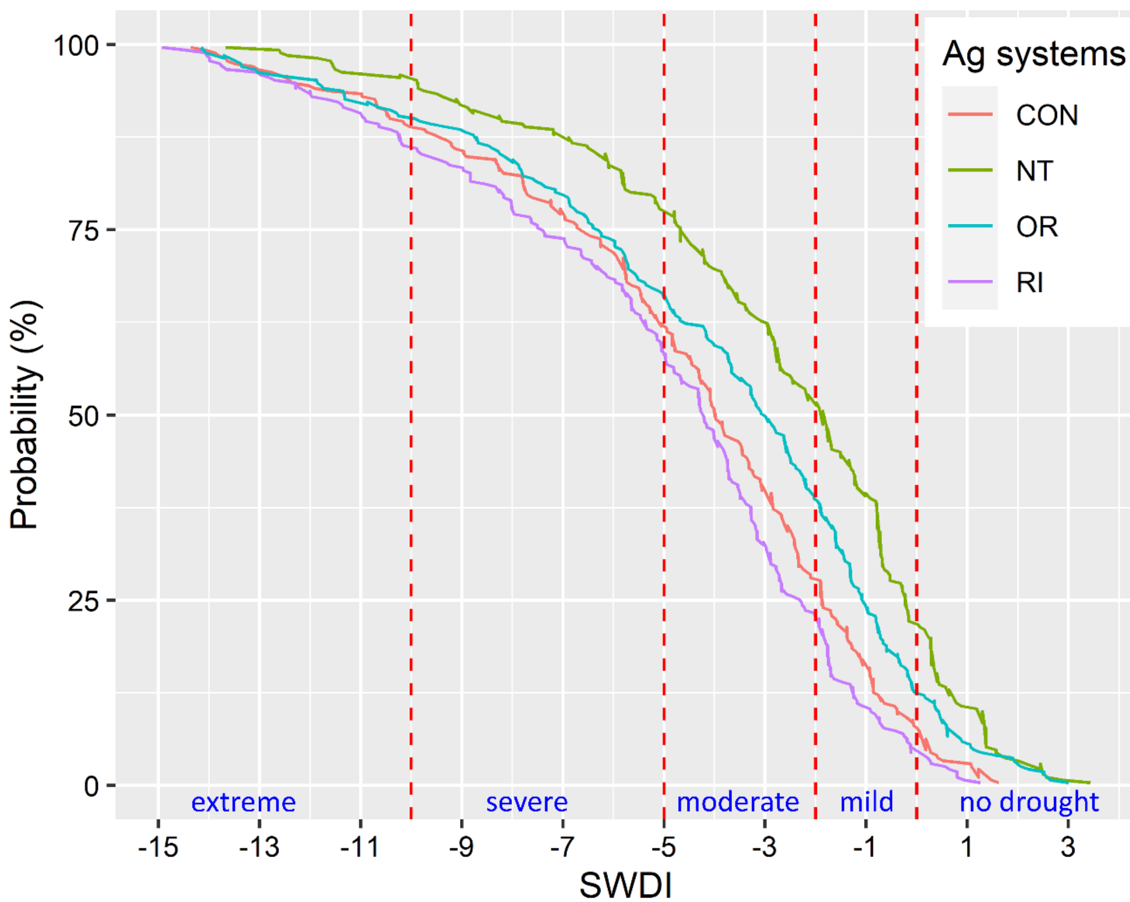

Figure 6. Probability distribution of drought experienced by each agricultural system as represented by SWDI during the experimental period (1993-2018). Note: Red dashed lines represent the boundary of different drought severity levels. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

Both of the above analyses have shown that the effectiveness of the no-till treatment to reduce moderate, severe, and extreme drought events is much greater than all other treatments. In agreement with these findings, Lal et al. (2012) showed that compared to the conventional system, the no-till system had 86 mm more available soil water at planting during drought-hit (2011-2012) in Akron, Colorado. This is due to greater soil water conservation under the no-till system as resulted by reduced runoff, evaporation rate, and increased capture of snow (Al-Kaisi et al., 2013; Lal et al., 2012). Furthermore, Thierfelder and Wall (2010) found three to five times higher infiltration for no-till plots compared to conventional plots in Africa. They argued that the no-till would increase the soil moisture and enable crops to mitigate the effects of droughts. Therefore, the effectiveness of the no-till treatment to reduce agricultural drought severity is much higher than the conventional treatment.

The organic treatment is inferior to the no-till treatment but superior to the conventional treatment on reducing moderate, severe, and extreme droughts. The primary reason for the higher effectiveness of the organic treatment to reduce agricultural drought compared to the conventional treatment could be due to higher water holding capacity of soils under the organic management (Lotter et al., 2003). In the temperate climate of Switzerland, water holding capacity was reported 20-40% greater in organically managed soils in comparison to those managed conventionally (Mäder et al., 2002). Pimentel et al. (2005) quantified 15-20% higher soil water availability in organic systems than the conventional systems in the long-term Rodale Institute Farming Systems trial in Pennsylvania. This is because of the presence of higher soil organic matter in organically managed soils, and it has been estimated that for every 1% soil organic matter, soil can hold 10,000-11,000 liters of plant-available water per ha of soil down to about 30 cm soil depth (Gomiero et al., 2011). In our organic treatment study, the soil organic matter was 0.3% higher than that in the conventional treatment, when soil organic carbon (Figure S3) converted to organic matter. Cover crops are grown under organic treatment also may have contributed to soil moisture conservation (Basche et al., 2016; Yang et al., 2020).

Finally, the effectiveness of the reduced input treatment to mitigate drought occurrences (moderate, severe, and extreme) is limited compared to other treatments (Figures 5 and 6). This may be due to its poor soil biology resulting from herbicide applications when compared to the organic treatment (Basche and DeLonge, 2019) and tillage operation compared to the no-till treatment. However, it was not clear why the reduced input treatment had lower effectiveness to reduce drought severity than the conventional treatment. These findings highlight that the no-till treatment is the best, the organic treatment is better, and the reduced input treatment is worst when compared to the conventional treatment in terms of the effectiveness of lowering agricultural drought.

4. Conclusions

In summary, this study showed that mean relative difference, the Spearman's rank correlation coefficient, and soil water deficit index are applicable in combination to evaluate resilience in different rainfed agricultural systems as related to the soil moisture content, growth, and yield. The no-till system had the highest resiliency than the conventional treatment in terms of higher soil moisture retention, higher effectiveness for drought mitigation, larger crop yields, and increased stability of yields. The yields in the no-till treatment were 15%, 18% and 4.3% greater than the conventional treatment for corn, soybean and wheat, respectively. Although the organic treatment had substantially higher resiliency in terms of grater soil moisture retention and drought mitigation than the conventional treatment, yields were significantly lower, especially for cereals (i.e., corn and wheat) as a result of nitrogen limitation. Even though the yields of corn and soybean in the reduced input treatment were comparable to those in the conventional treatment, the reduced input treatment had the limited capacity to recover from extreme conditions and improve resiliency in terms of soil moisture retention and drought mitigation. Finally, the proposed approach here can be improved in future studies by increasing the frequency of soil moisture measurements over the growing season at different depths of the root zone. In addition, we are recommending the expansion of the study to larger spatial scales to better capture the robustness of these metrics under a variety of rainfed agriculture systems in the USA and around the world.

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6. Disclaimer

Any opinions, findings, conclusions, or recommendations expressed in this manuscript are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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Supplementary Materials

Evaluating the Applicability of Soil Moisture-based Metrics for Gauging the Resiliency of Rainfed Agricultural Systems in the Midwestern United States

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Table S1. Details of the four annual row crop treatments of MCSE investigated in this study

Treatment	Description of Management
Conventional (CON)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was used from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Fertilizers were applied at the rates based on soil-test recommendations for each crop. Herbicides were broadcasted within and between rows to control weeds. There were no applications of manure/compost or insecticides.
No-till (NT)	Crops were planted in corn-soybean-winter wheat rotation. These crops were established under zero tillage. Fertilizers were applied at rates based on soil-test recommendations for each crop. Herbicides were broadcasted within and between rows to control weeds. There were no applications of manure/compost or insecticides.
Reduced input (RI)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was used from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Nitrogen (N) fertilizer and herbicide inputs were applied as one-third of N and herbicides applied to the conventional system (Reduced input). These herbicides were banded within rows. Winter cover crop was established following the corn and wheat crops within the rotation with the intention of supplementing nitrogen to the following crop. Generally, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted after wheat. There were no applications of manure/compost or insecticides.
Organically managed (USDA certified organic) (OR)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was performed from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Winter cover crop was established following the corn and wheat crops within the rotation with the intention of supplementing nitrogen to the following crop. Generally, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted after wheat.. This certified organic treatment was not applied with any chemical fertilizers/herbicides/insecticides.

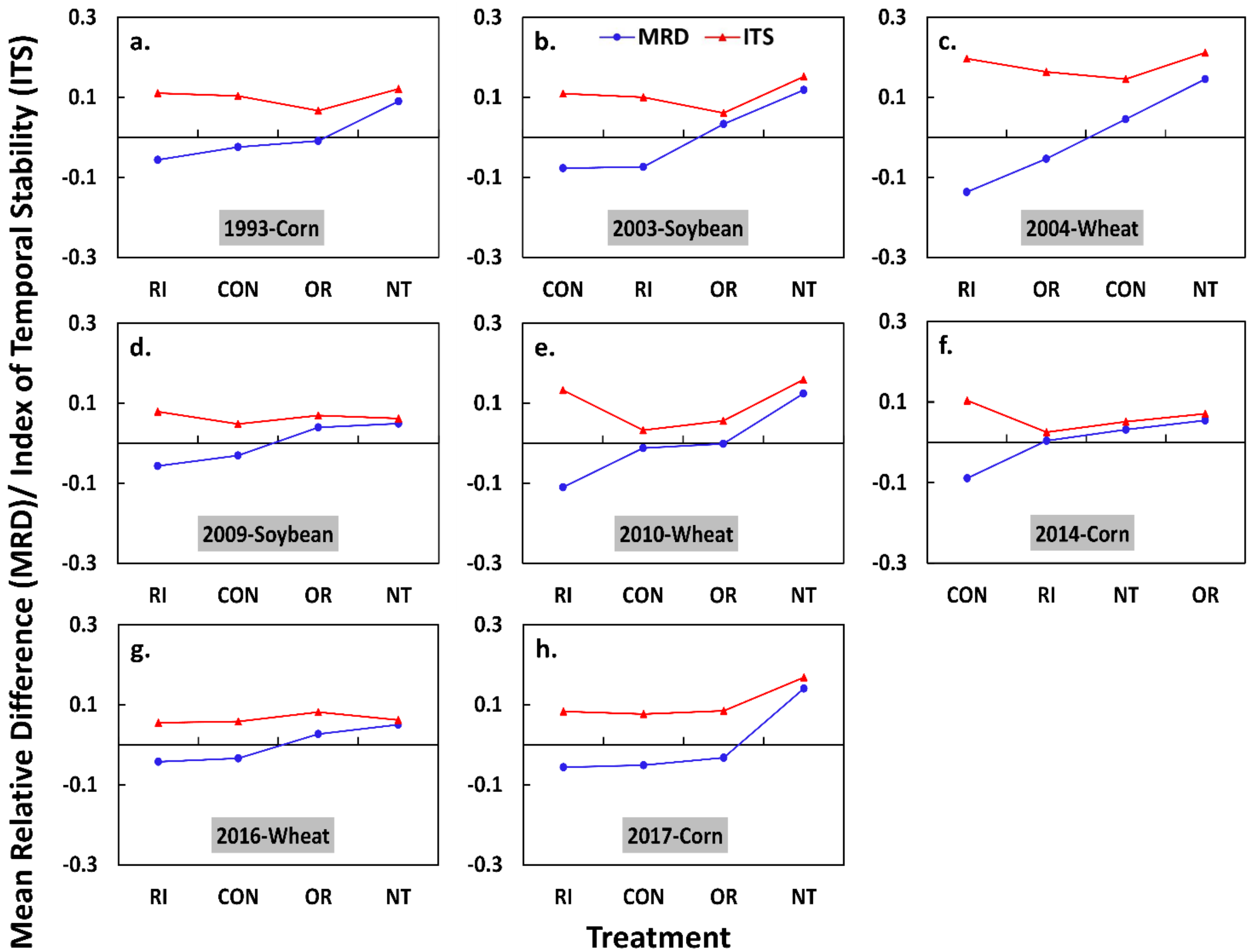

Figure S1. Ranked MRD of volumetric soil moisture and ITS for each treatment during the normal years. Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

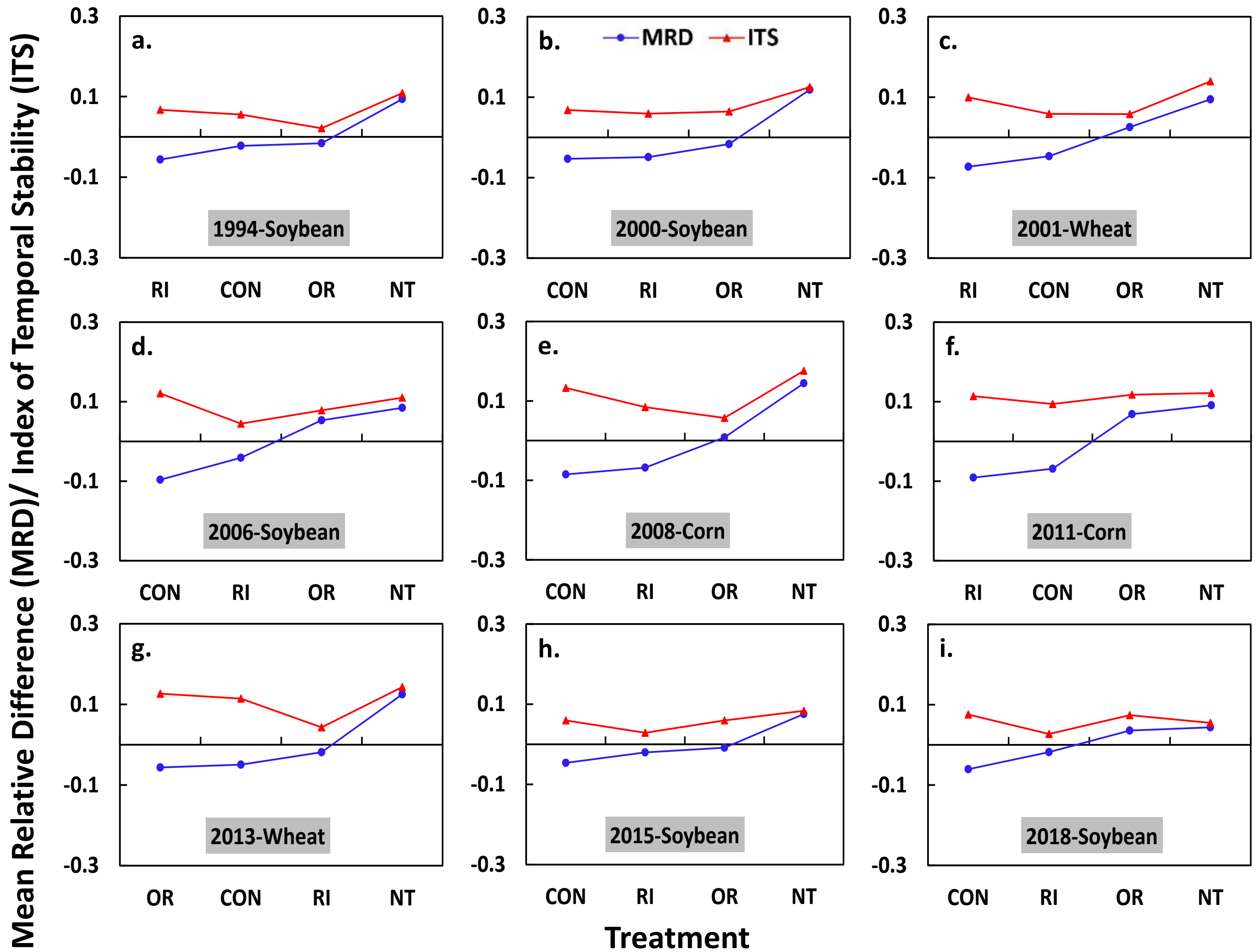

Figure S2. Ranked MRD of volumetric soil moisture and ITS for each treatment during the wet years. Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

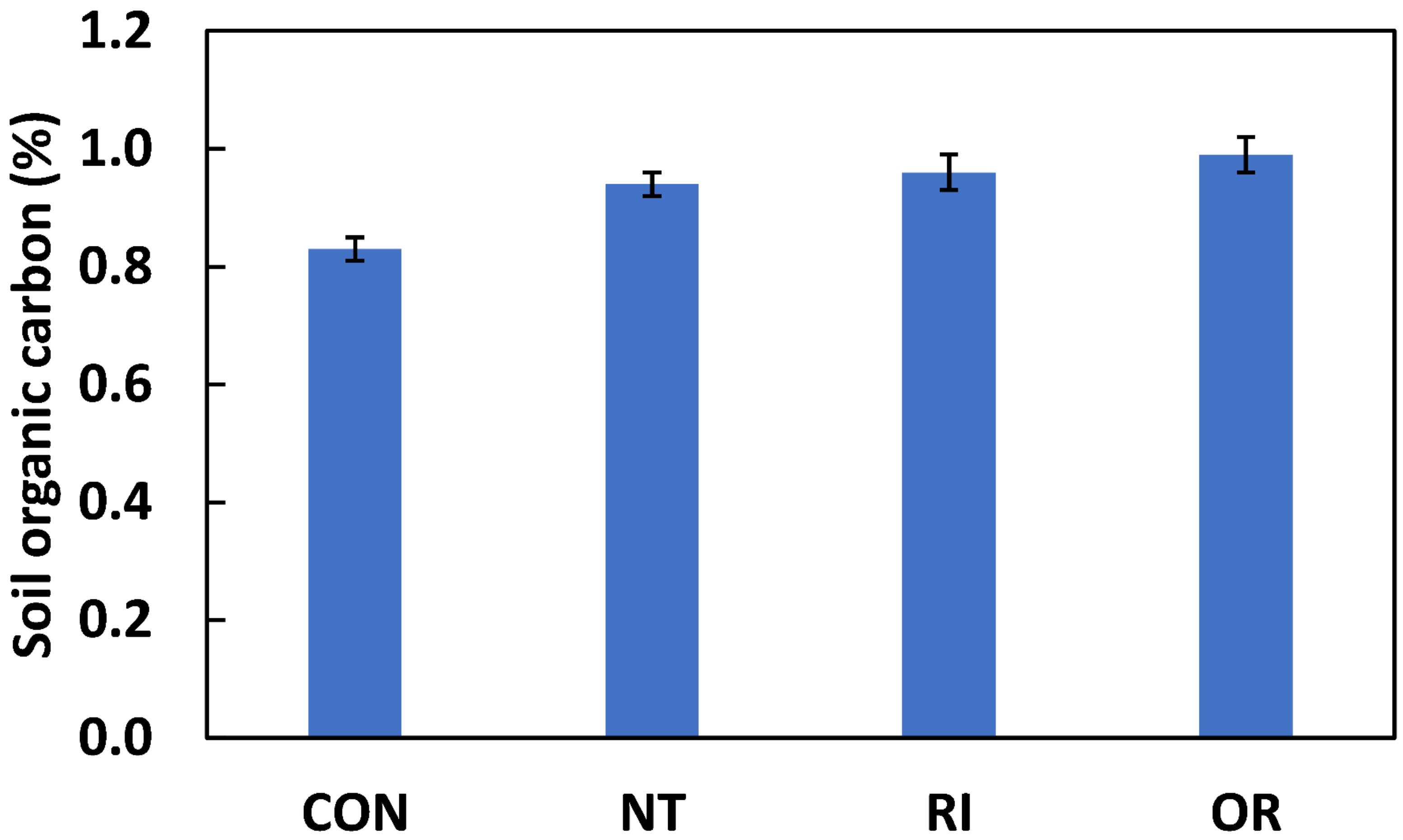

Figure S3. Means of soil organic carbon content in different treatments during the period of 1989-2001 in this experiment. The error bars represent the standard error. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

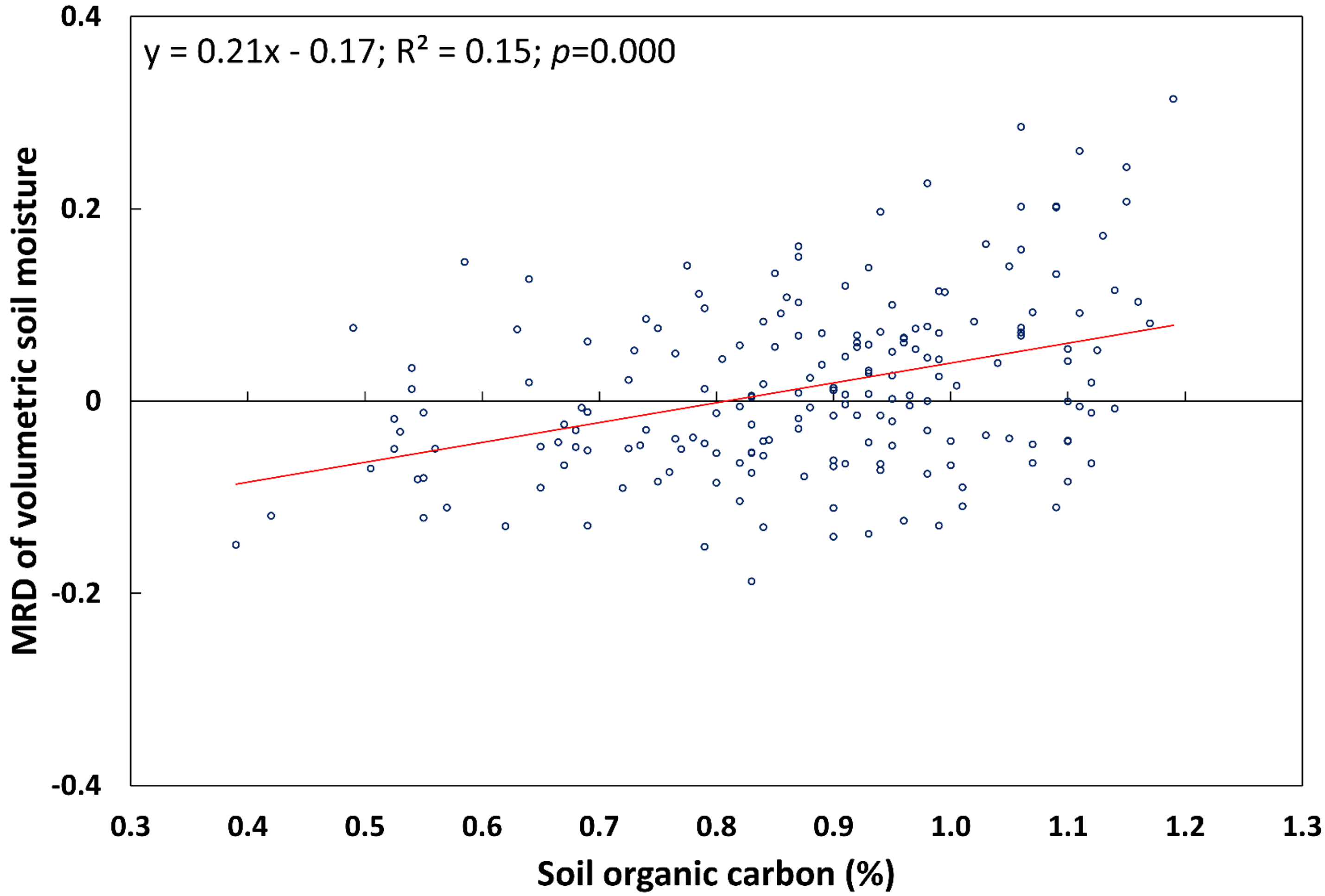

Figure S4. Association between mean relative difference (MRD) of volumetric soil moisture and soil organic carbon content in the treatments investigated in this study.

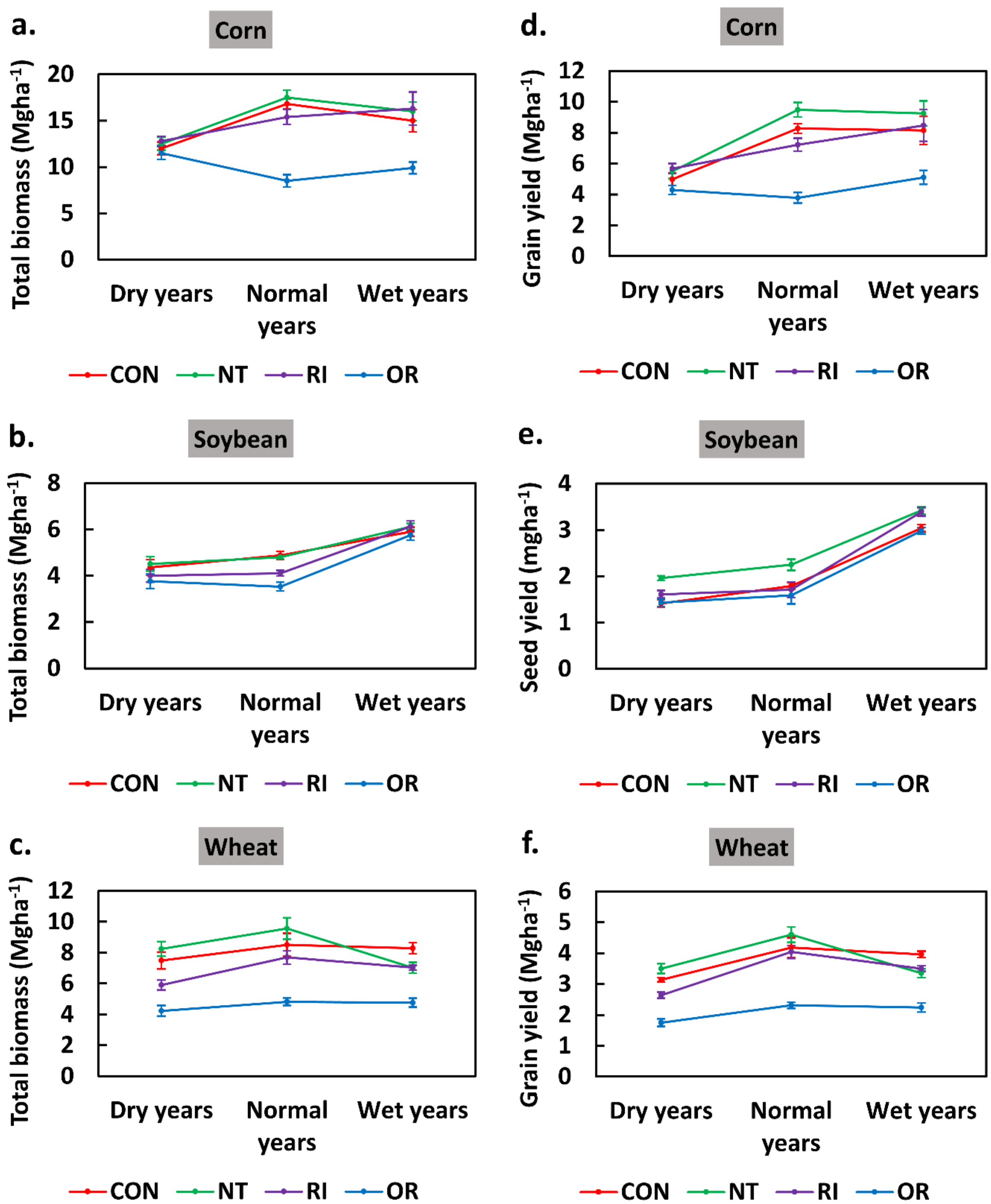

Figure S5. Total biomass (a-c) and yield (d-f) of crops as affected by the interaction between treatment and climate variability. The error bars represent the standard error. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.

Table S2. *P*-values for the effects evaluated in the statistical mixed model for MRD, total biomass and yield

Crop	Effects in the statistical model	Probability (*p*-value)		
		MRD	Total biomass	Yield
Corn	Treatment (*trt*)	<0.0001**	<0.0001**	<0.0001**
	Climate variability (*clim*)	0.9250	0.5154	0.2641
	Year (*yr*)	>0.05	0.0563	0.0948
	Interaction between treatment and climate variability (*trt* × *clim*)	0.1733	0.0002**	0.0003**
	Interaction between treatment and year (*trt* × *yr*)	0.2497	0.0171*	0.0043*
Soybean	Treatment (*trt*)	<0.0001**	0.0020*	0.0198*
	Climate variability (*clim*)	0.9998	0.0024*	<0.0001**
	Year (*yr*)	>0.05	0.0845	0.0867
	Interaction between treatment and climate variability (*trt* × *clim*)	0.1442	0.0071*	0.0031*
	Interaction between treatment and year (*trt* × *yr*)	0.4661	0.6700	0.8306
Wheat	Treatment (*trt*)	<0.0001**	<0.0001**	<0.0001**
	Climate variability (*clim*)	0.9805	0.7511	0.2335
	Year (*yr*)	>0.05	0.0698	0.0729
	Interaction between treatment and climate variability (*trt* × *clim*)	0.8305	0.3534	0.1965
	Interaction between treatment and year (*trt* × *yr*)	0.8107	0.0700	0.0640

**Strongly significant at $p<0.001$; *significant at $p<0.05$.

Table S3. Coefficient of variation of total crop biomass and yield of crops under different treatments as affected by climate extremes

Crop parameter	Category of climate extreme	Treatment	Coefficient of variation (%)		
			Corn	Soybean	Wheat
Total crop biomass	Dry year	CON	28.1	26.3	30.9
		NT	19.0*	22.6*	21.0*
		RI	25.1	24.0	22.7
		OR	31.9	28.1	35.4
	Wet year	CON	27.9	18.6	15.1
		NT	20.0*	11.6*	16.6
		RI	38.1	21.2	7.4*
		OR	22.1	20.2	21.0
Crop yield	Dry year	CON	38.4	19.0	17.7
		NT	27.7*	7.8*	10.0*
		RI	39.3	16.9	16.2
		OR	33.2	18.3	28.4
	Wet year	CON	38.6	13.6	8.9
		NT	28.9*	12.3*	13.4
		RI	42.2	15.0	8.5*
		OR	30.7	13.0	23.5

*Lowest coefficient of variation for the total crop biomass and yield within each climate extreme.